

Digital Soil Mapping – Menace, Myth or Miracle?

Featured Content

Introduction

DSM

DSM - Florida

Summary



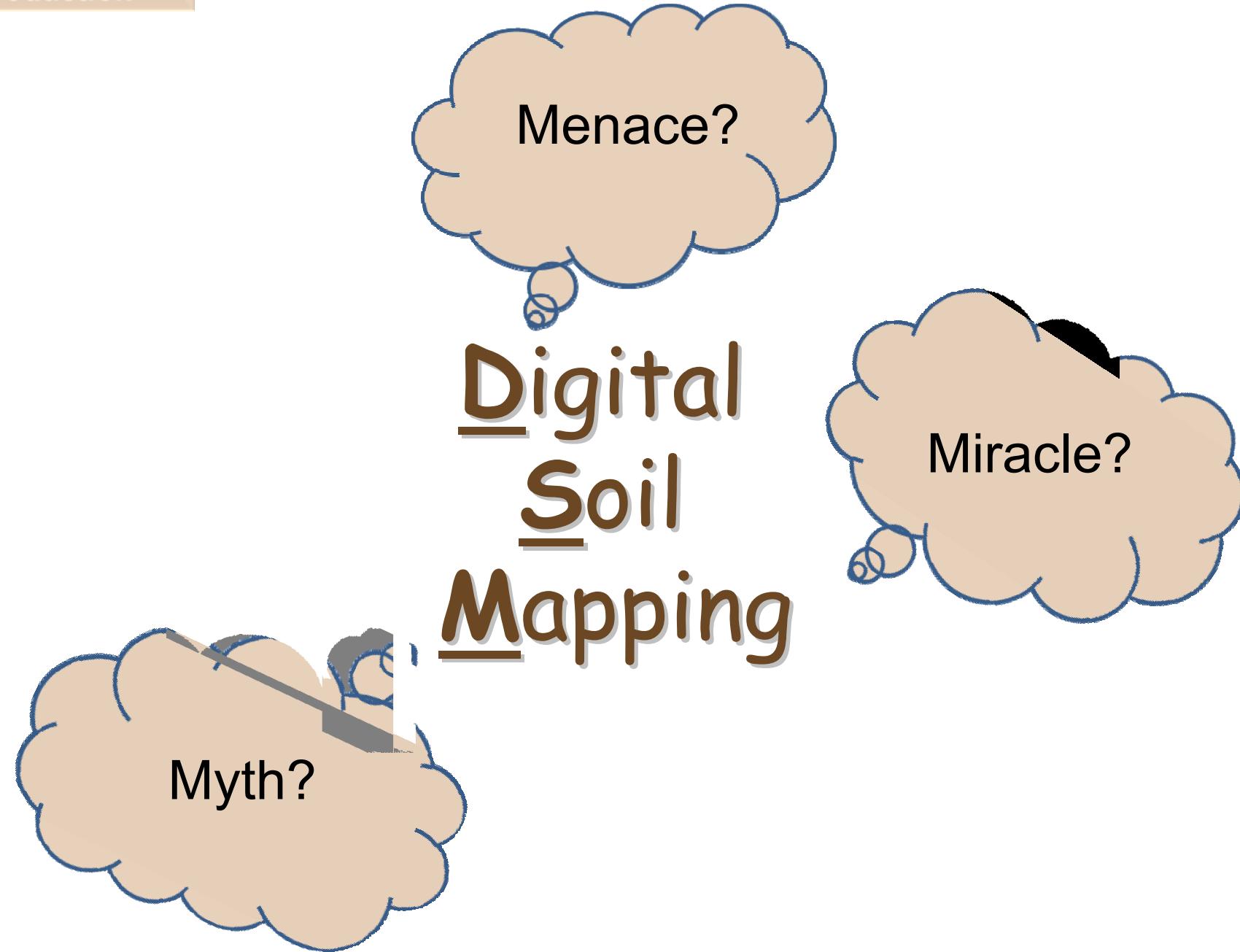
UF UNIVERSITY of
FLORIDA

Soil & Water Science Department, University of Florida

GIS Research Lab

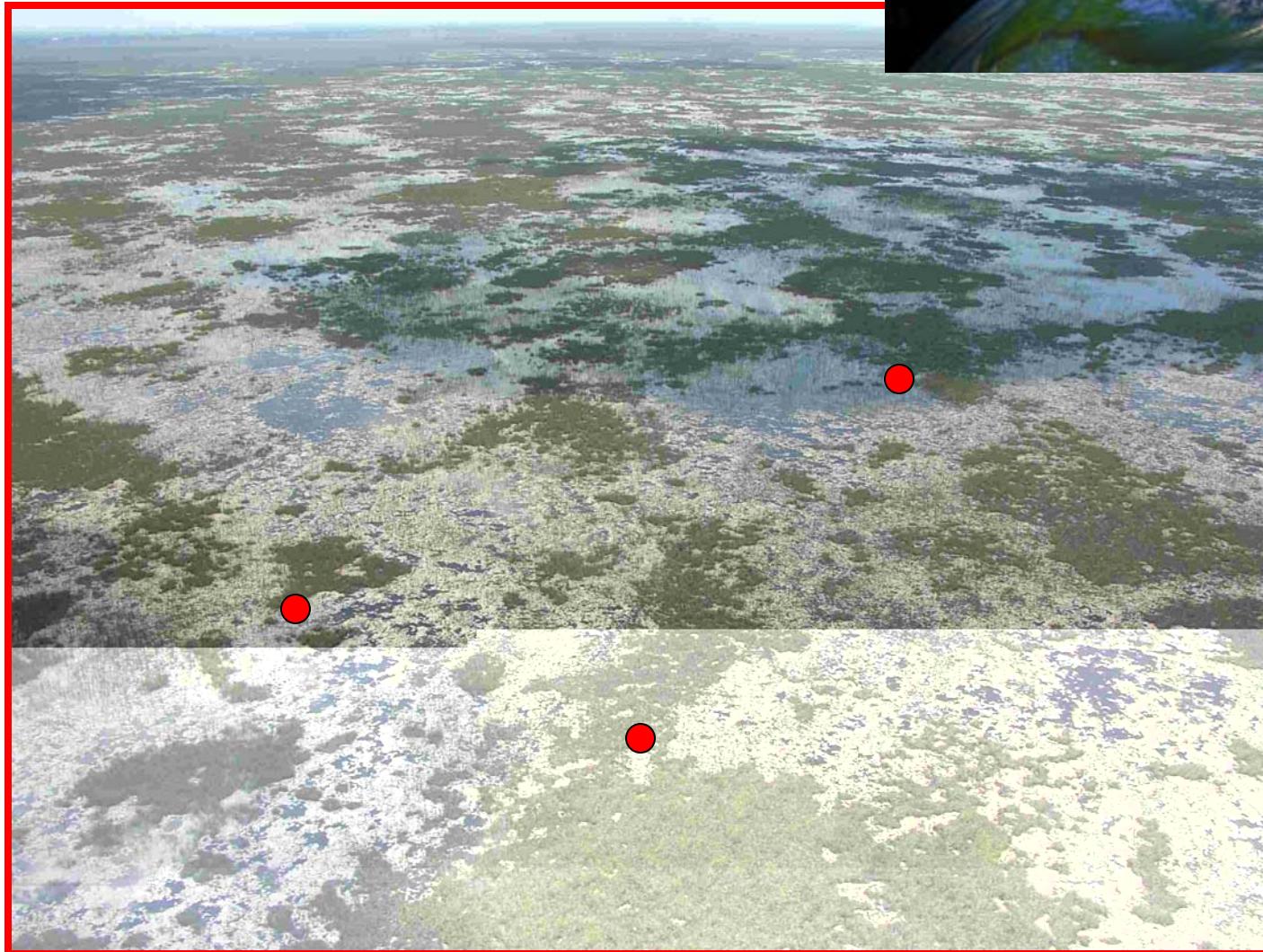
Authors





Introduction

Window of Perception

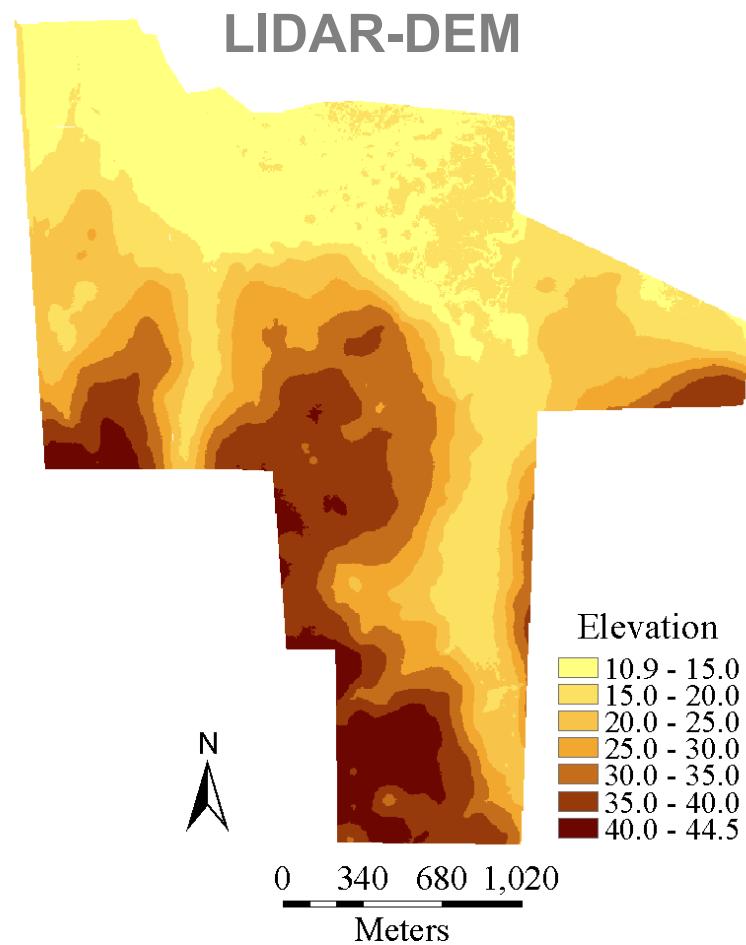


Introduction

Window of Perception



IKONOS
satellite imagery
(1-4 m spatial resolution)

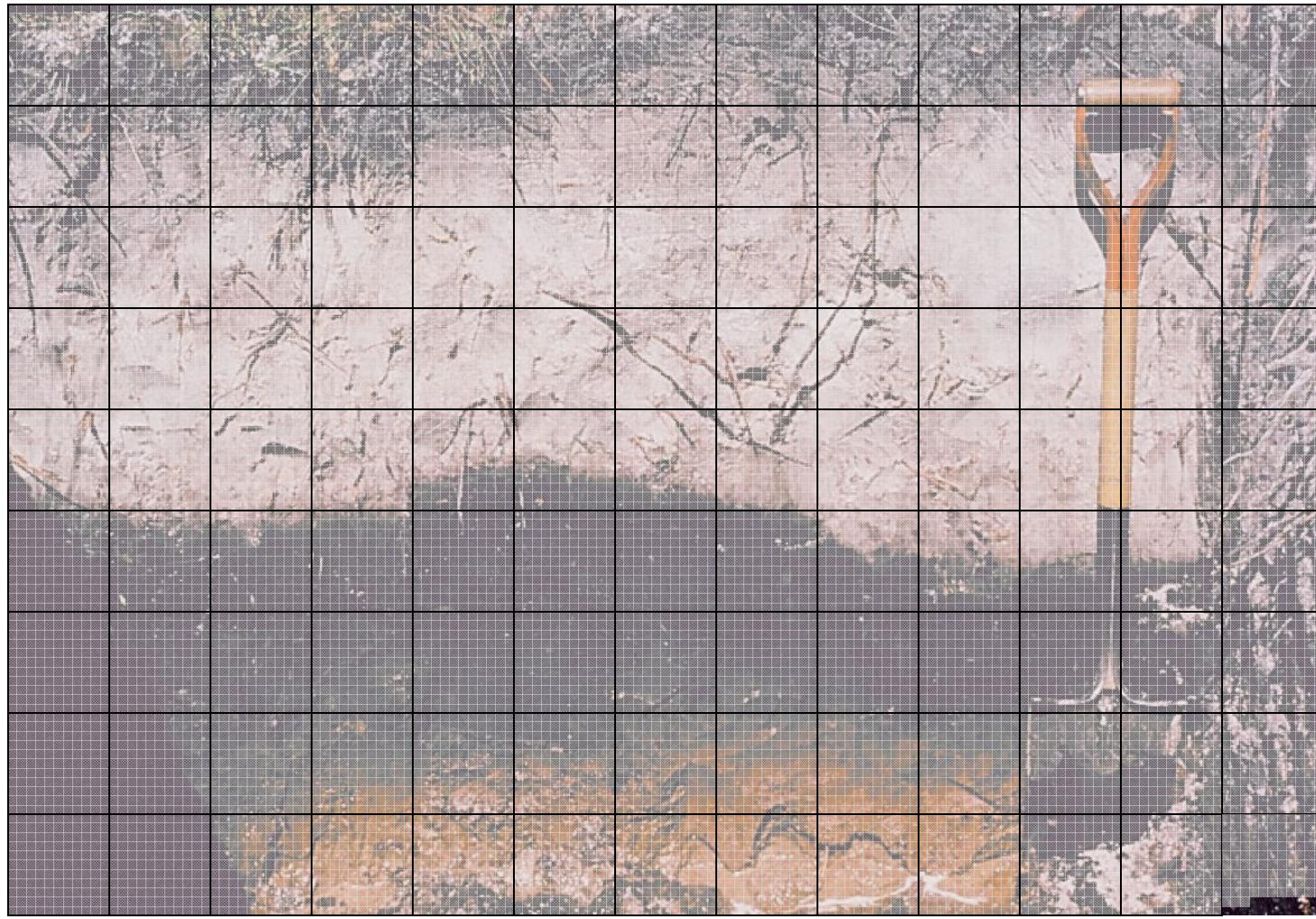


Introduction

Window of Perception



Mandarin, Clay County (photograph W.G. Harris)



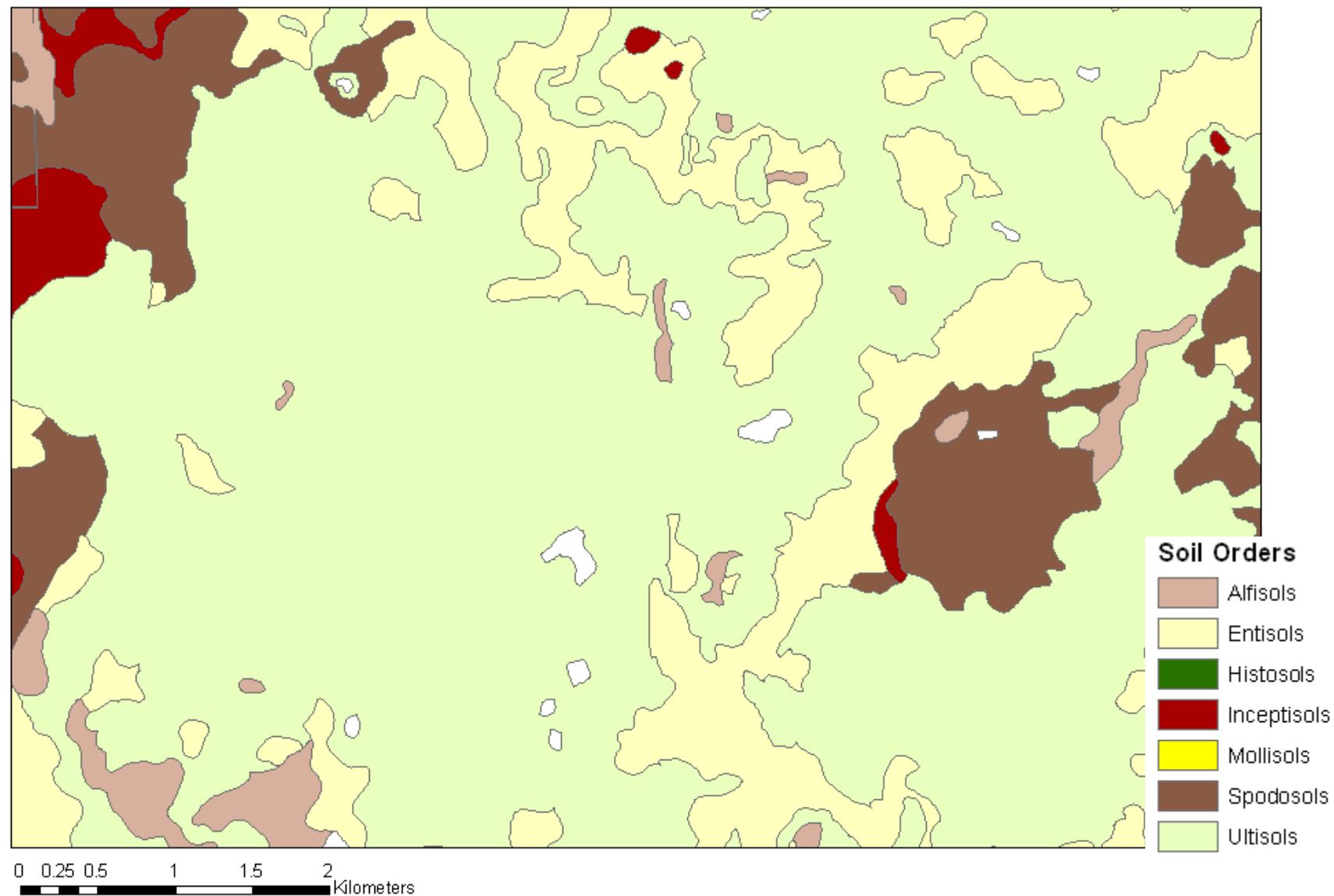
Mandarin, Clay County (photograph W.G. Harris)



Mandarin, Clay County (photograph W.G. Harris)

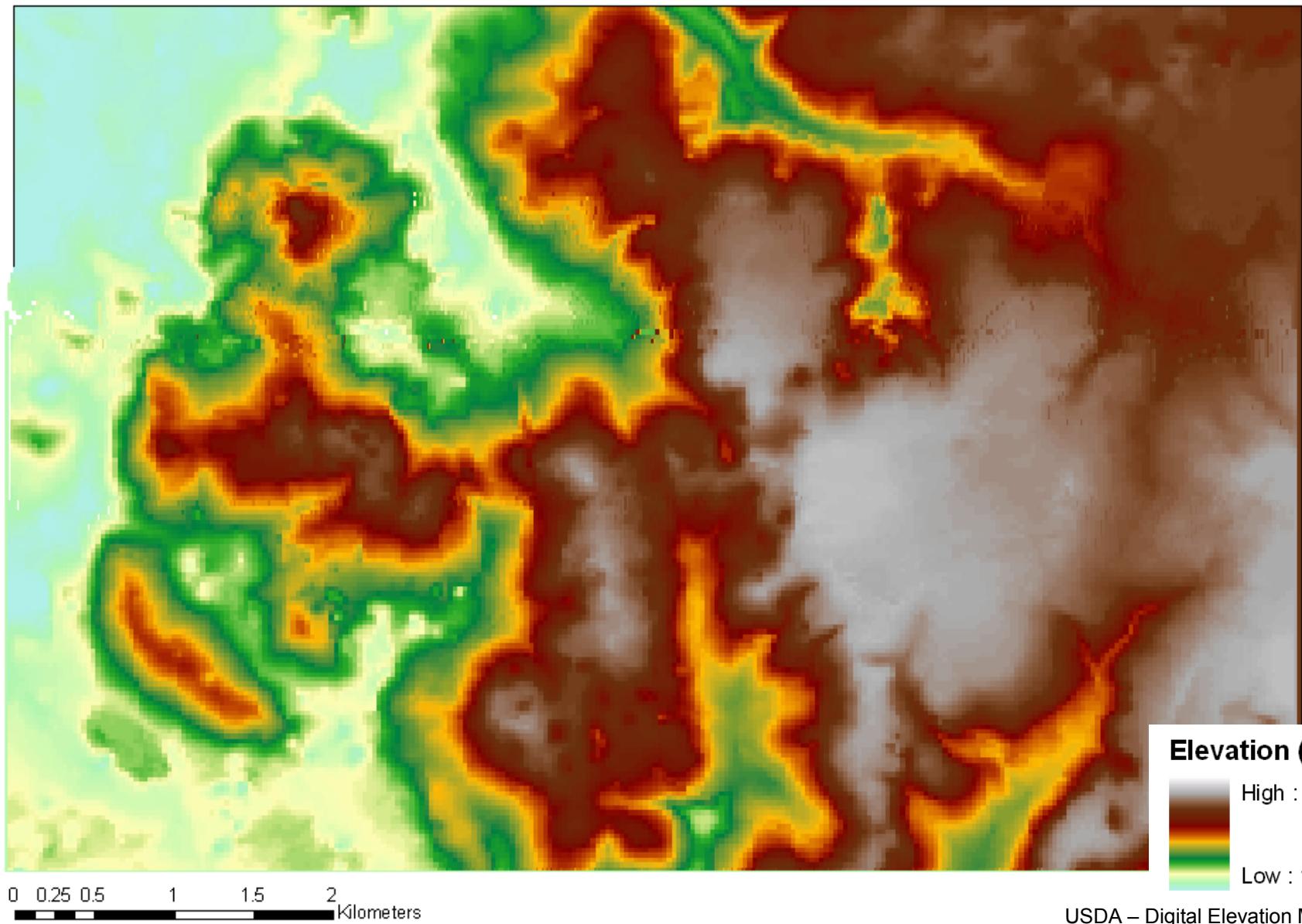
Window of Perception

Snapshot – Soil Data Mart (1:24,000) Columbia County – Soil Orders and map units



Window of Perception

Snapshot – same area Elevation (30 m spatial resolution)

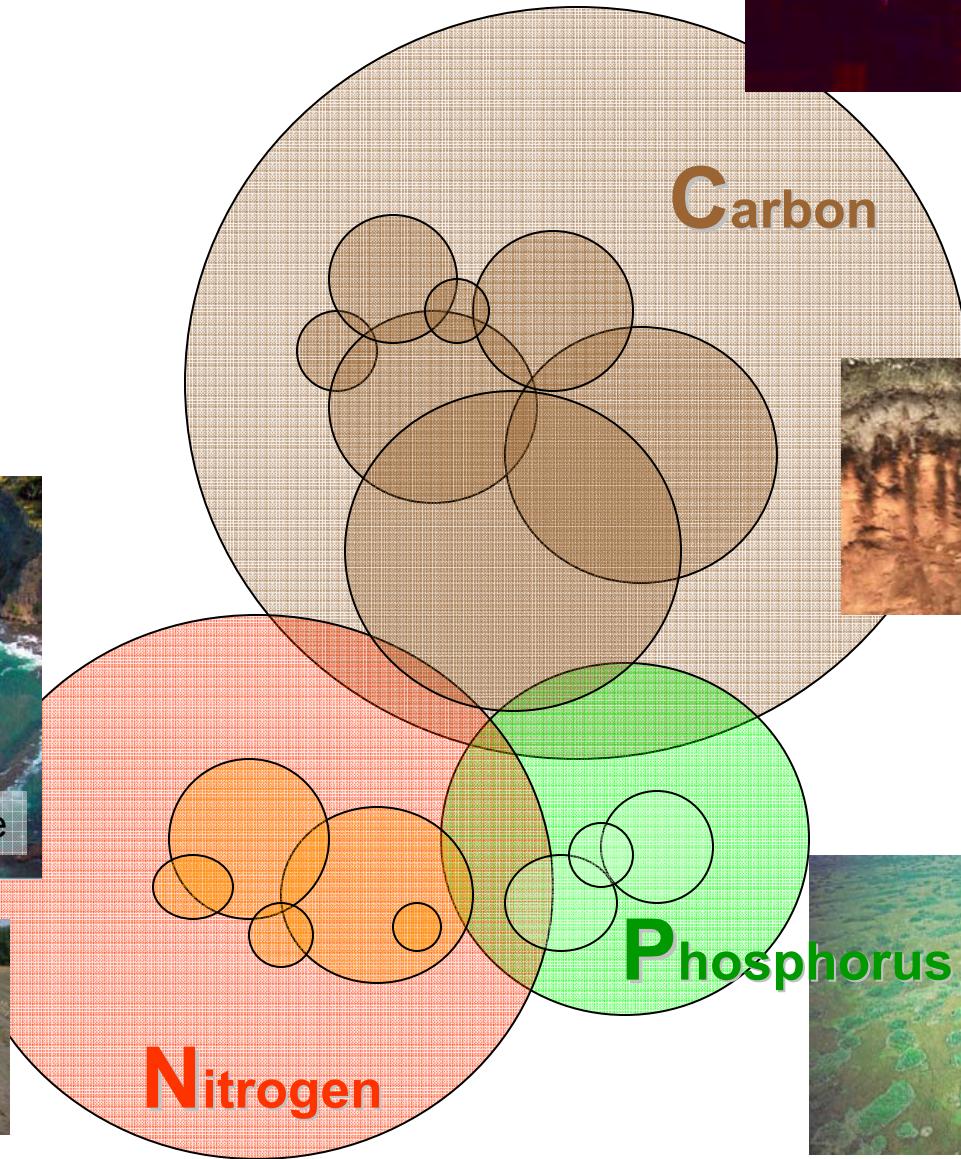


Introduction

Needs – Soil Data



Red tide



DSM

Soil Prediction Models

Global trend model

$$m(x_i)$$

+

Spatially autocorrelated model

$$\varepsilon(x_i)$$

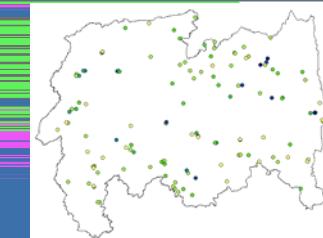
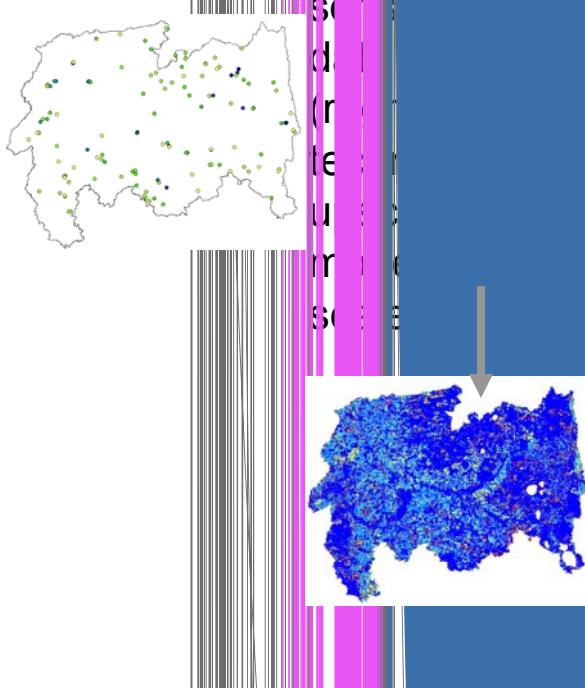
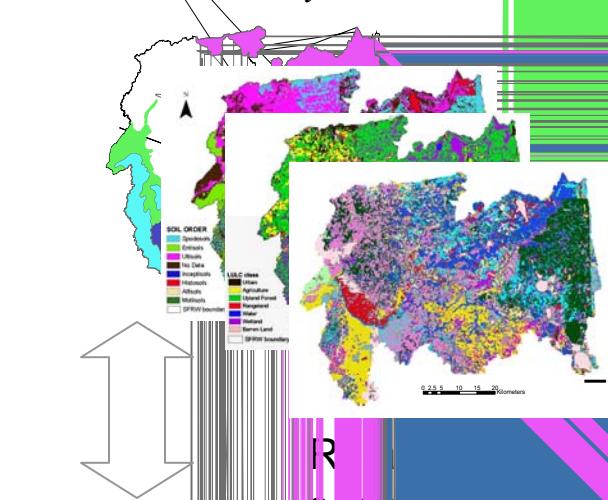
Error term

+

$$\varepsilon'$$

Prediction

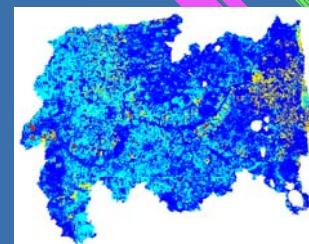
$$\hat{Z}(x_i)$$



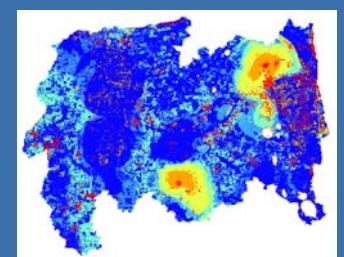
Site-specific soil data
(e.g. soil P)
• labor intensive
• costly

Characterize the spatial
variability and distribution
of soil attributes using
variography and
geostatistics

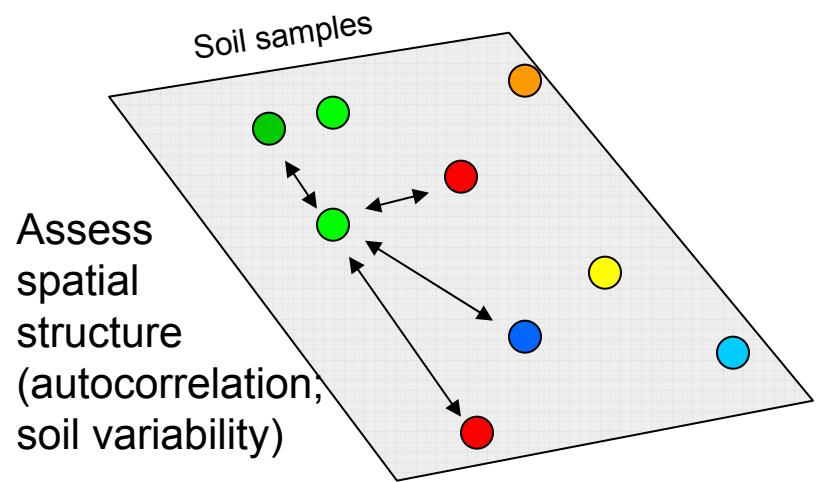
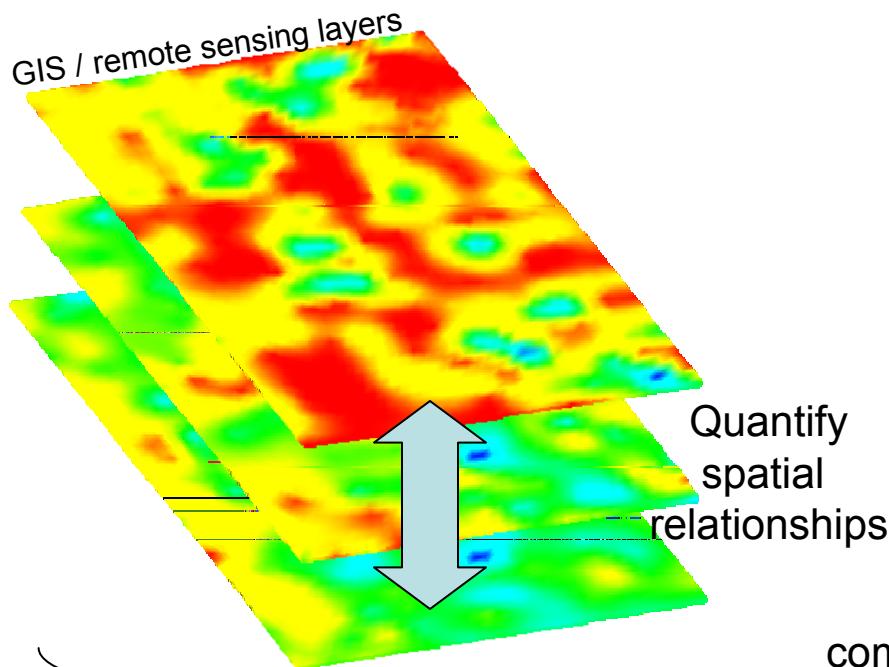
+



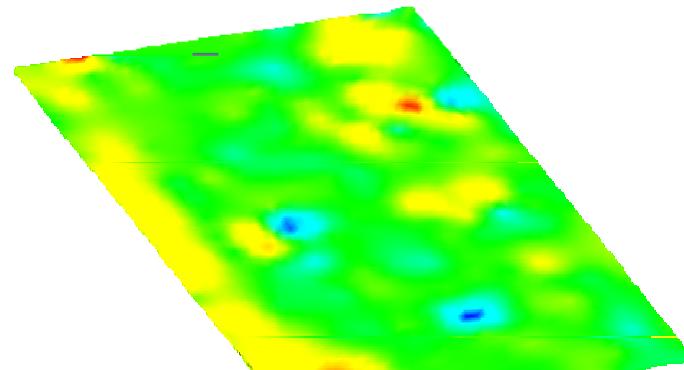
=



Predicted
soil variable



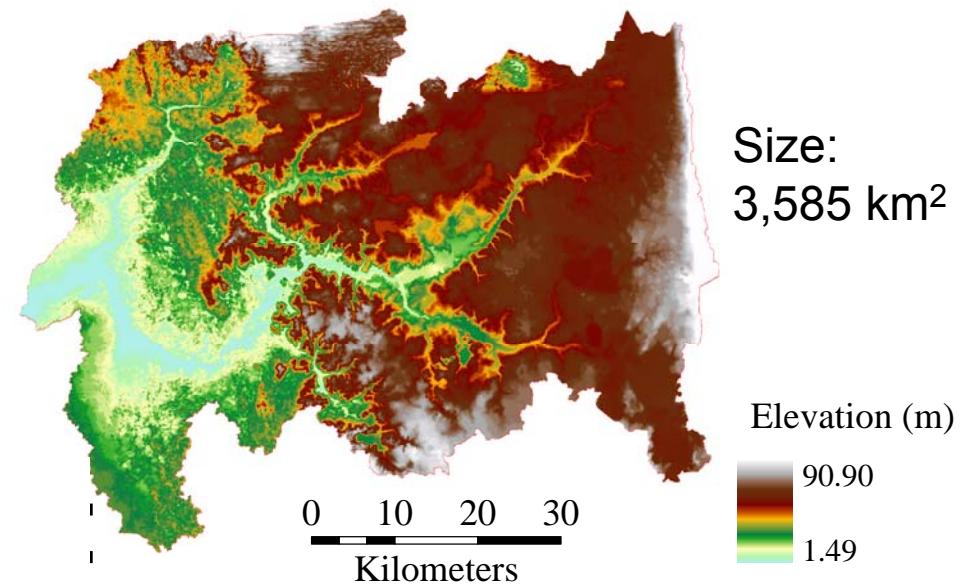
combine



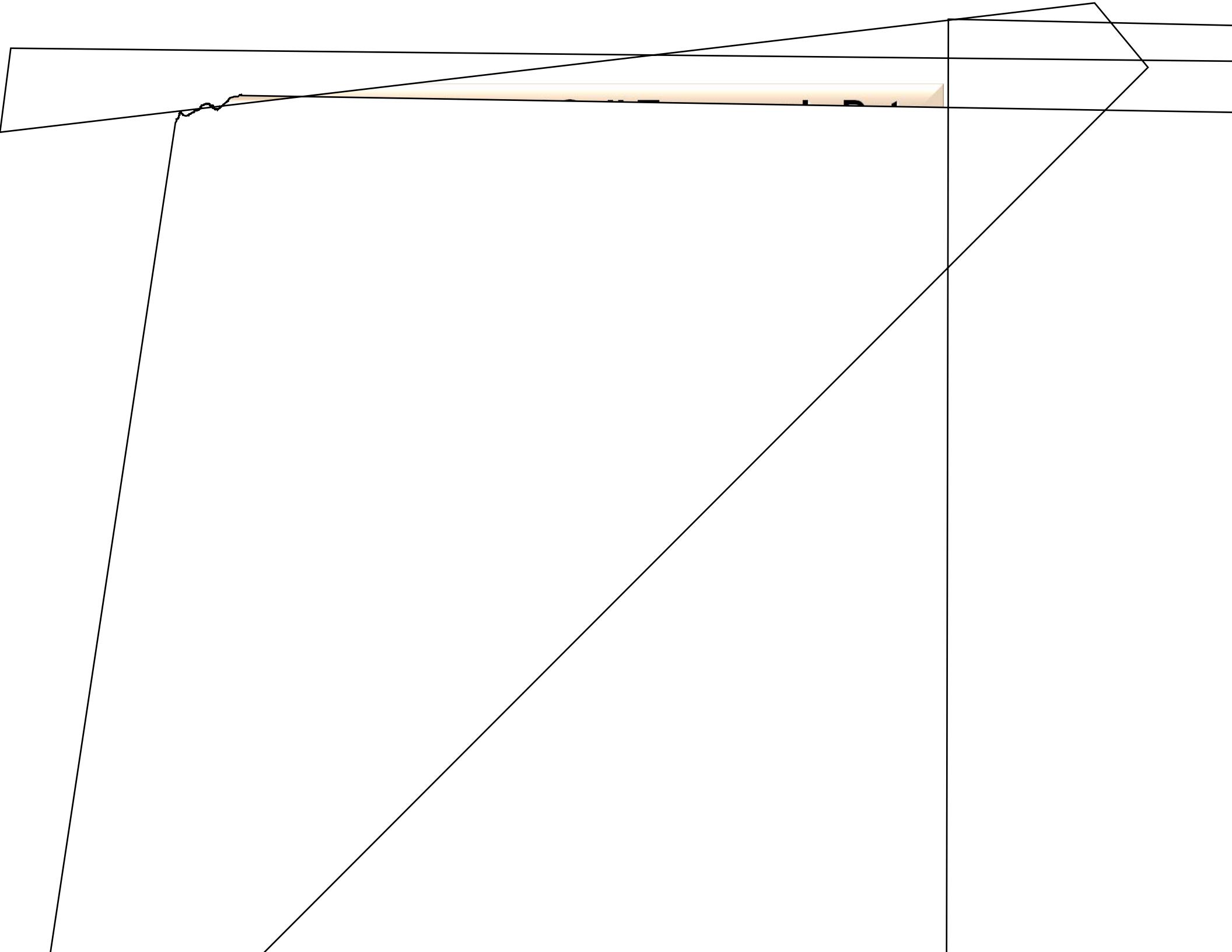
Prediction of Soil Taxonomic Data

Objective:

Predict Soil Orders across the Santa Fe River Watershed, Florida

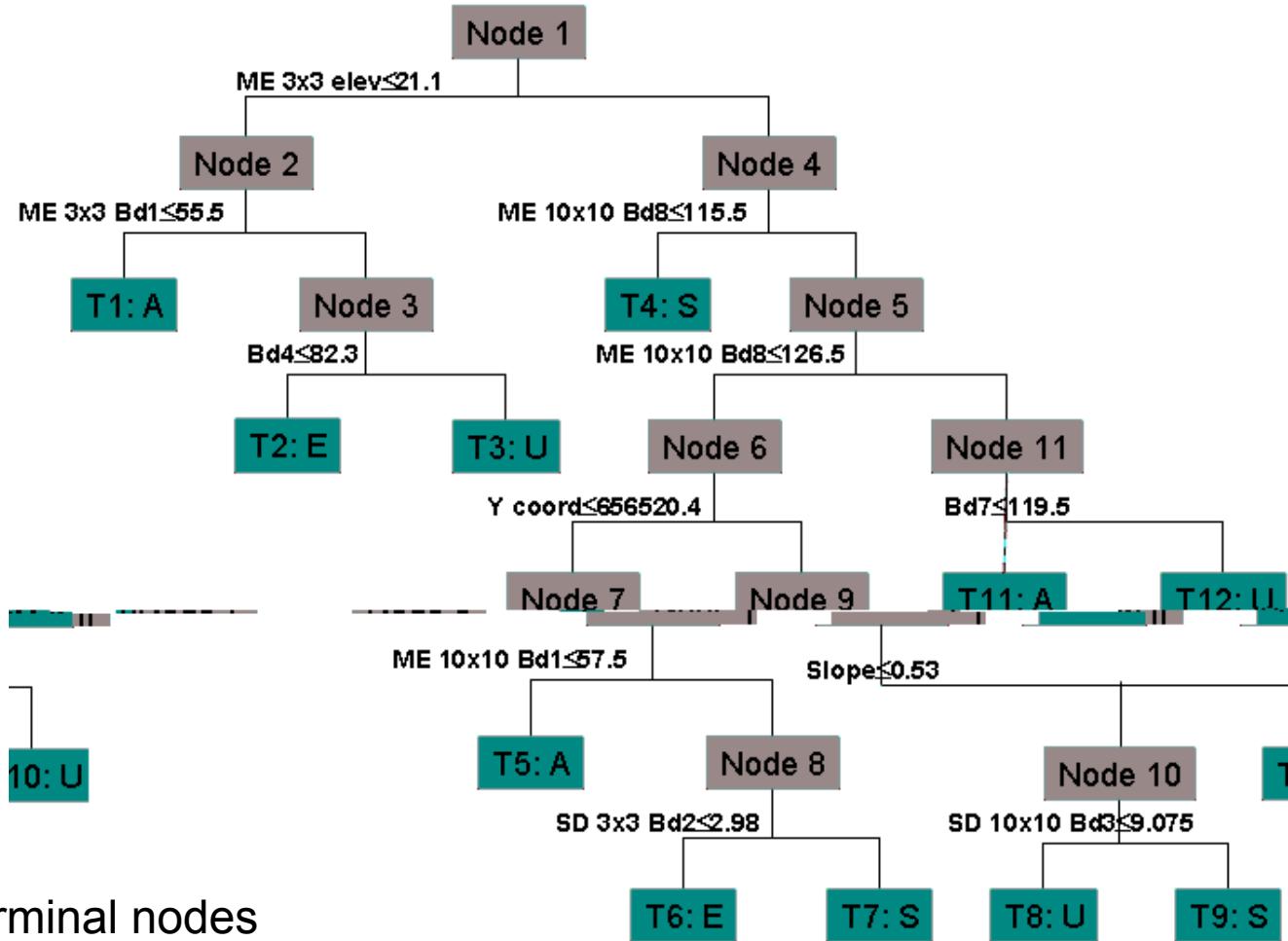


Grunwald S., G.W. Hurt, G.L. Bruland, and N.B. Comerford. 2006. SCORPAN-based soil-landscape modeling in north-east Florida. World Congress of Soil Science - Frontiers of Soil Science, Philadelphia, Pennsylvania, July 9-15, 2006.



Prediction of Soil Taxonomic Data

Tree-model to predict Soil Orders



(mode: CLORPT-lfg;
bagging with 250 trees)

Results - Prediction performance of Soil Orders (10 V-fold Cross Validation)

R^2 : 0.9

% correct Alfisols: 0.0

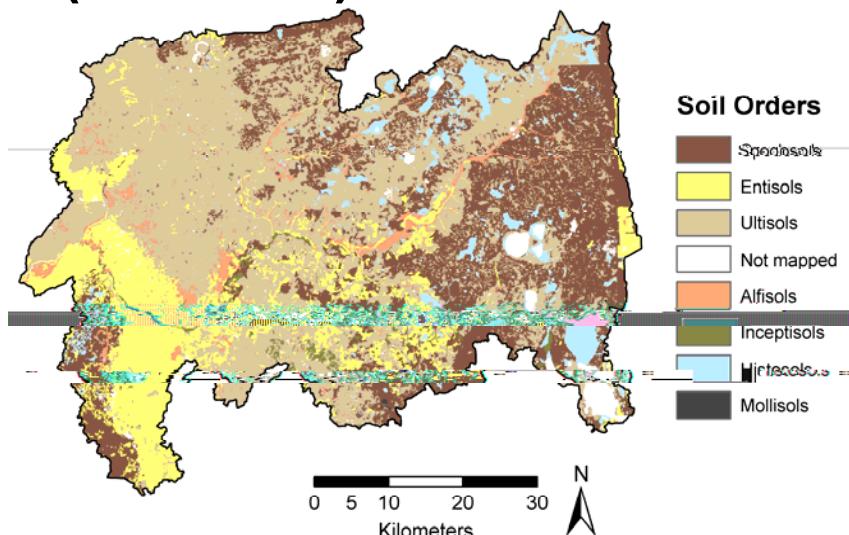
% correct Entisols: 50.0

% correct Spodosols: 60.0

% correct Ultisols: 83.3

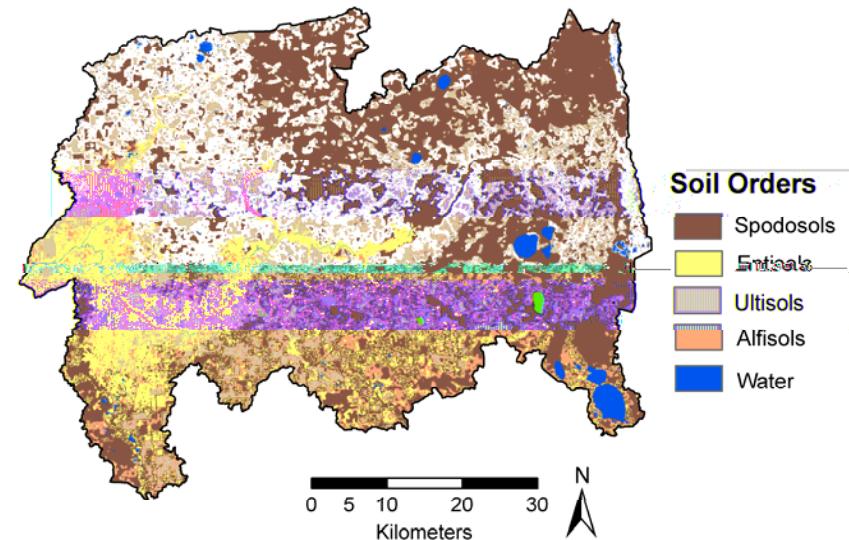
Prediction of Soil Taxonomic Data

NRCS – Soil Data Mart (1:24,000)



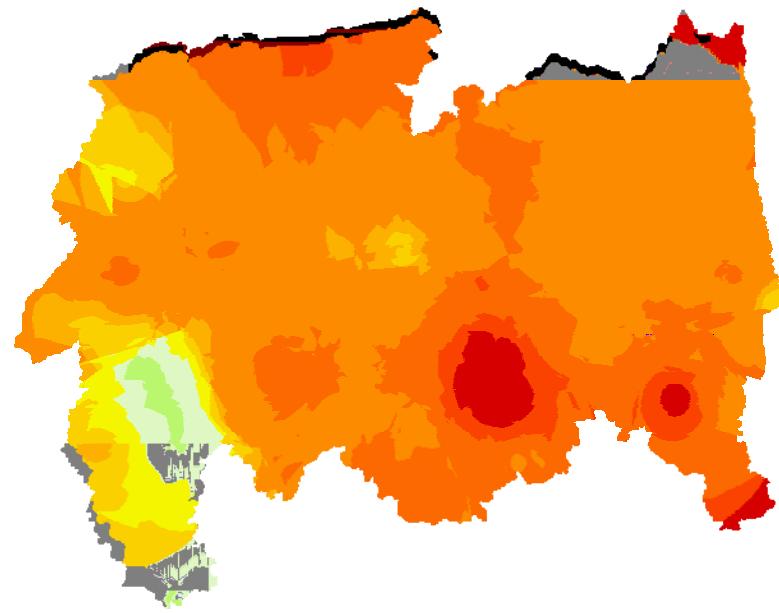
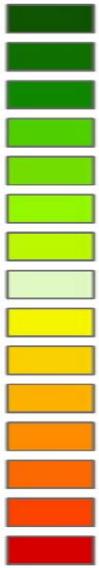
Coverage of soil orders:
46.5% Ultisols,
26.6 % Spodosols,
16.5 % Entisols,
4.3 % Histosols, 2.8% Alfisols, 1.0 % Inceptisols, and 2.2% Unknown.

Predictions (30 m resolution)



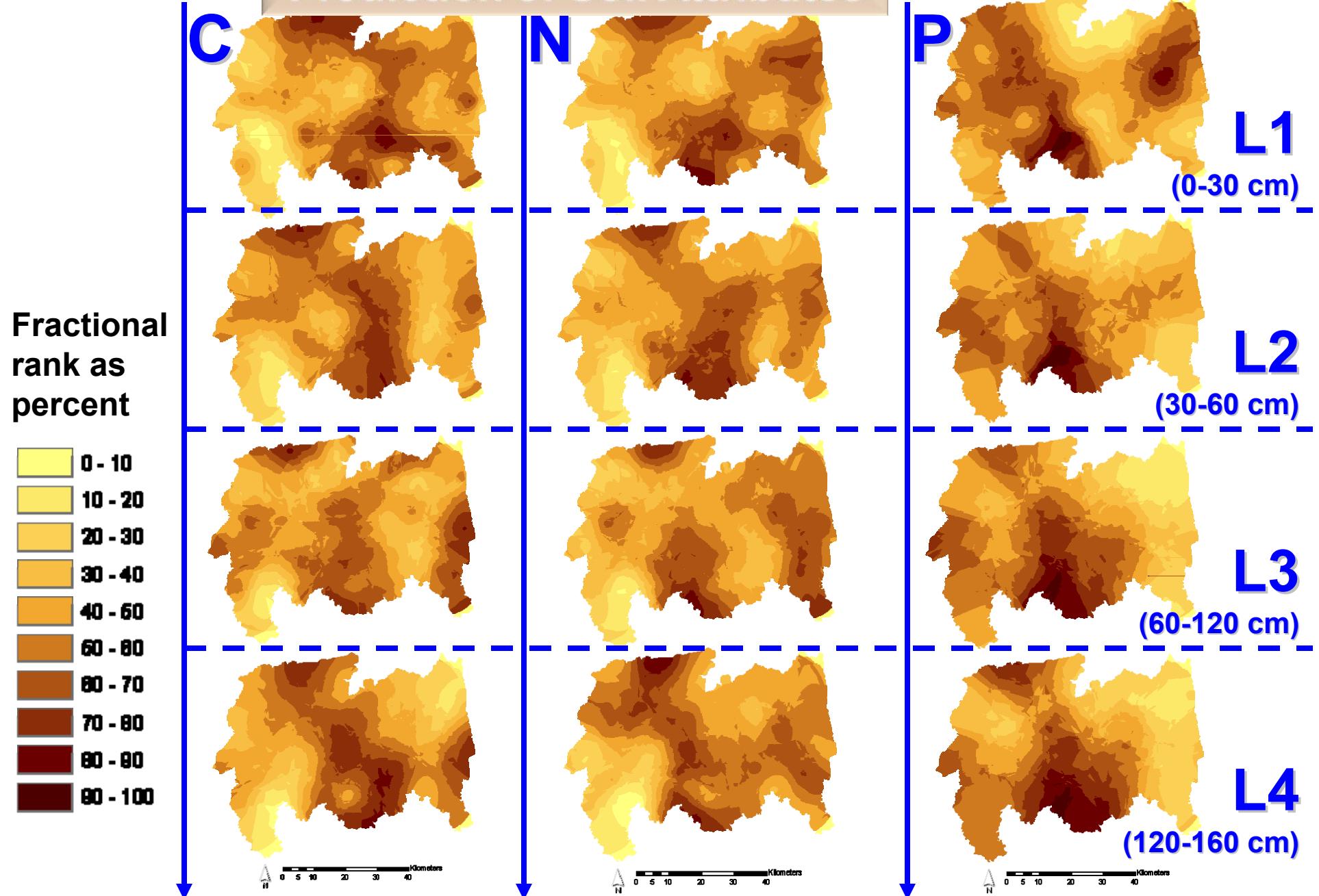
Soil Orders were predicted covering an area of about 81% of the watershed with
16.0% Ultisols,
40.6% Spodosols,
15.6% Entisols,
and 9.2% Alfisols.

C (mg/kg)



DSM - Florida

Prediction of Soil Attributes

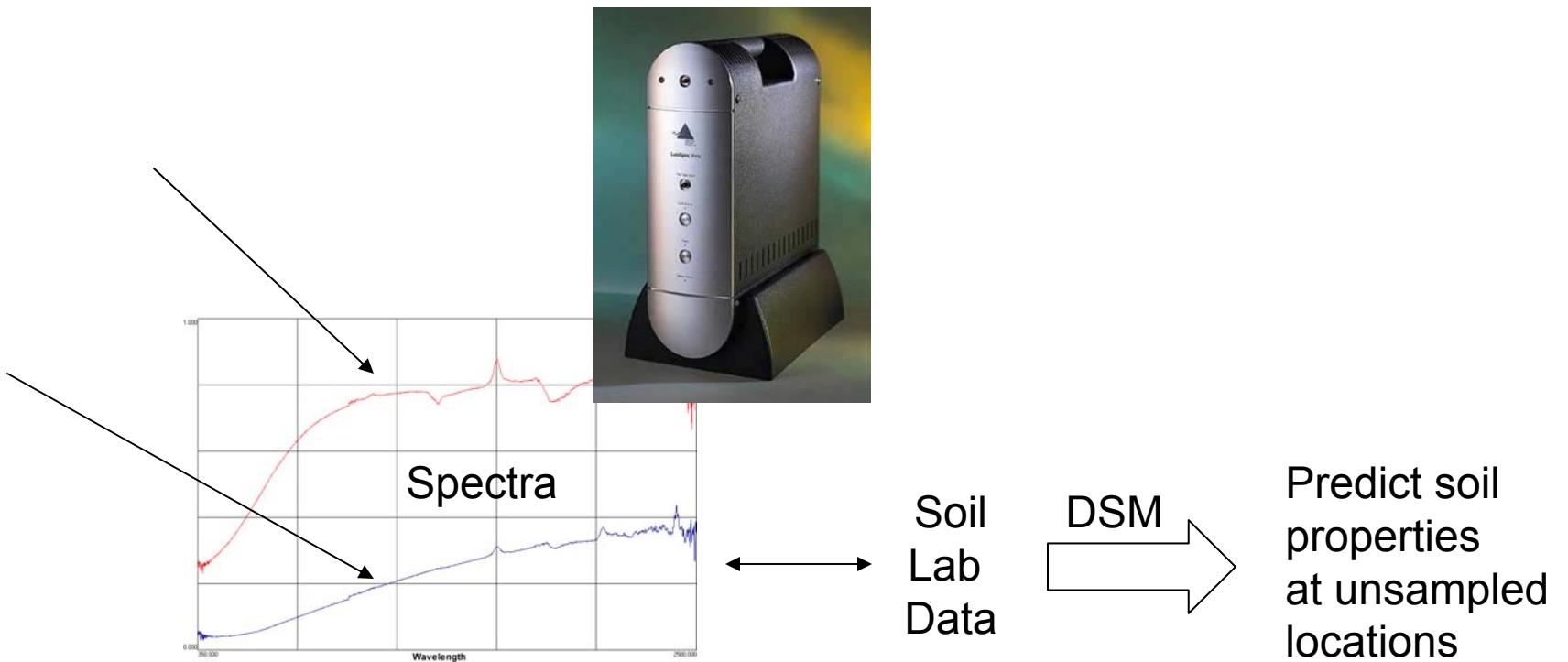


VNIR – Soil Sensing

VNIR – Visible/Near-Infrared Spectroscopy

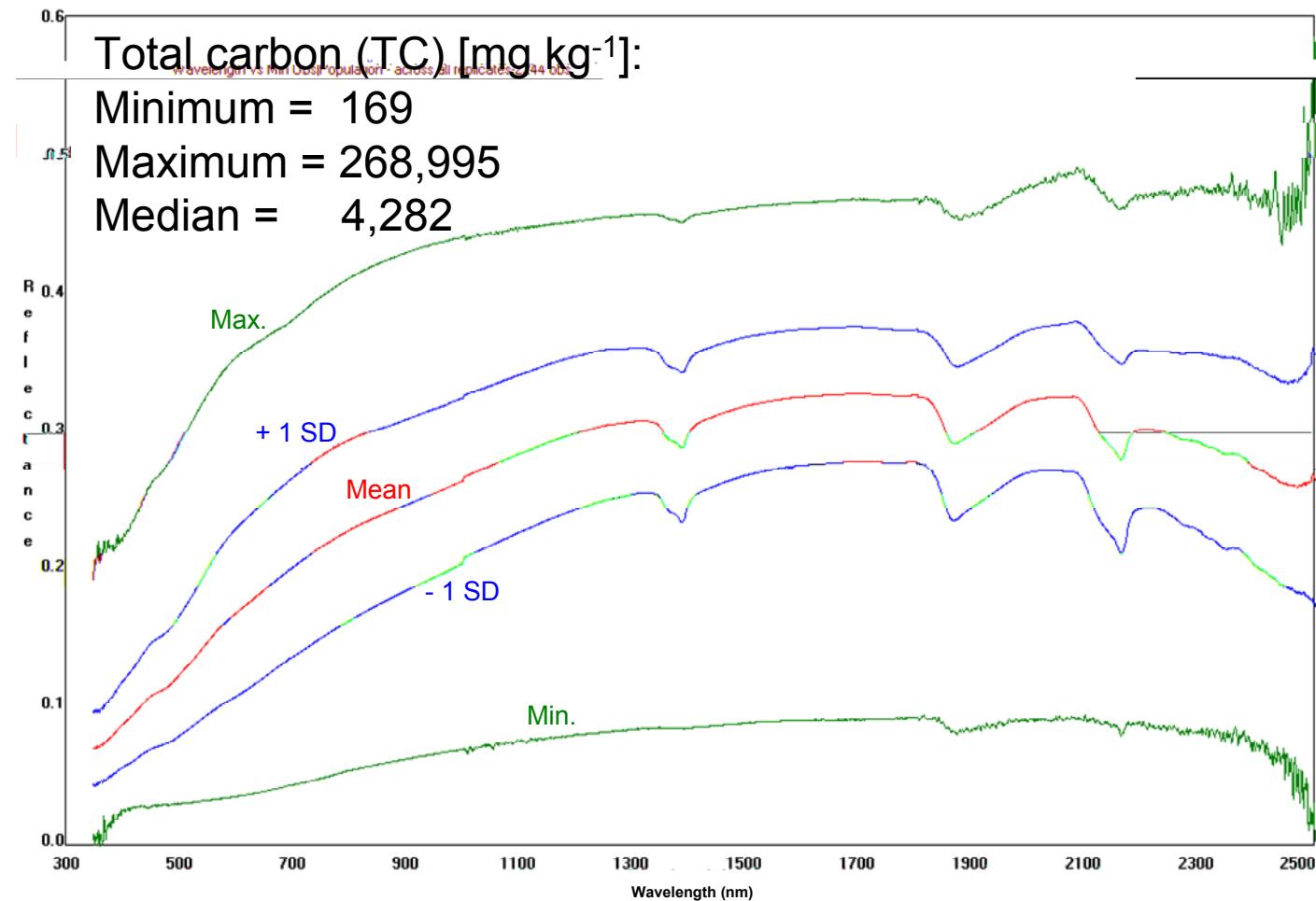


Objectives:



VNIR – Soil Sensing

Spectral scans of 554 soil samples collected in the SFRW at 4 different soil depths (0-30, 30-60, 60-120 and 120-180 cm)



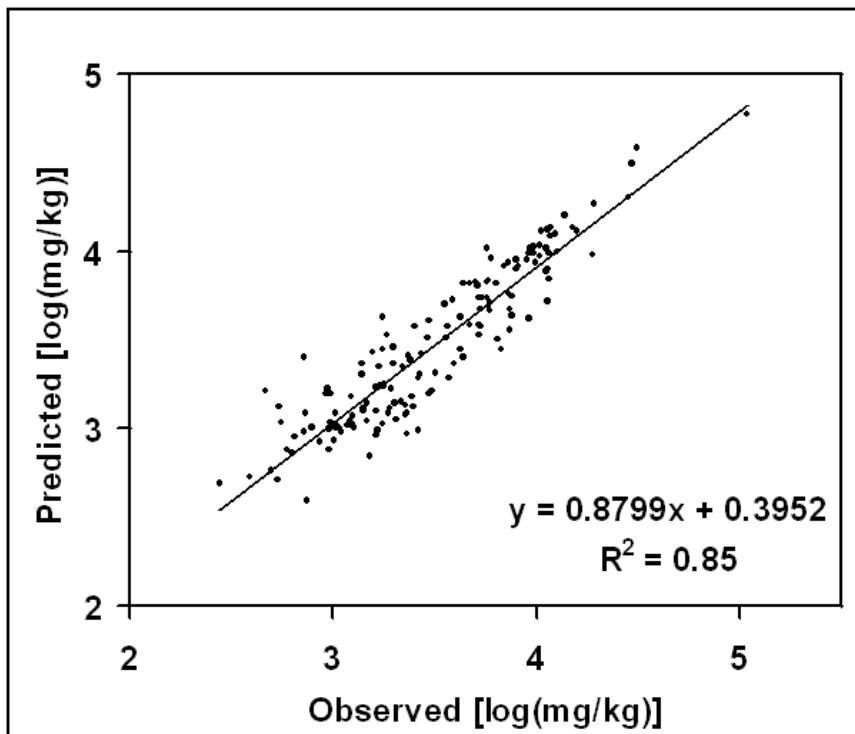
Funded by
NRCS-CESU

Vasques G.M., S. Grunwald, and J.O. Sickman. 2008. Comparison of multivariate methods for inferential modeling of soil carbon using visible/near-infrared spectra. Geoderma (in press).

VNIR – Soil Sensing Validation Results

PLSR

(Method: Partial Least Squares Regression)



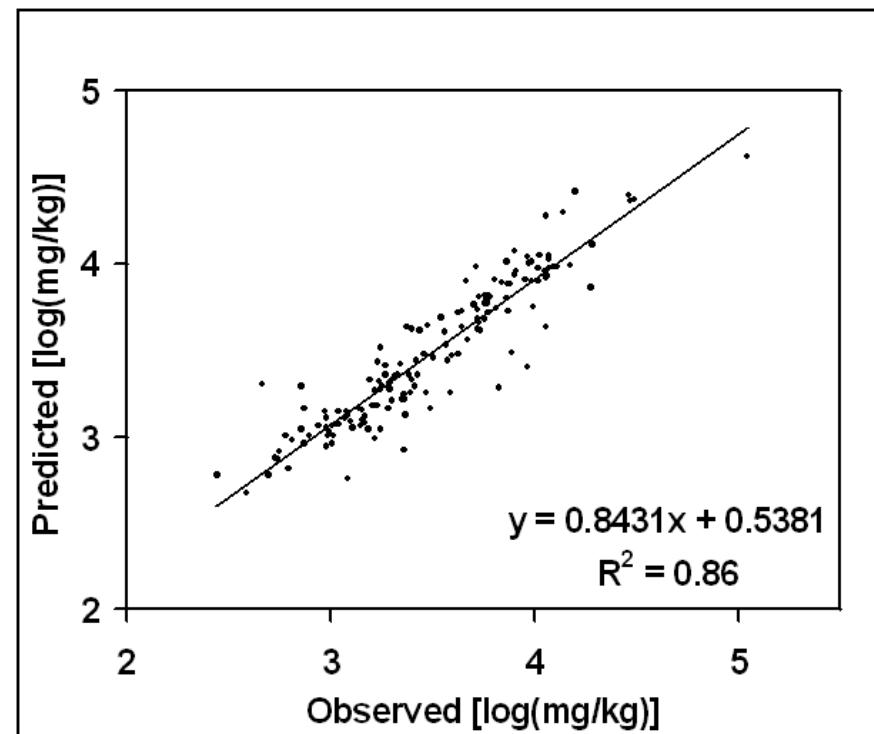
[pre-processing: Savitzky-Golay 1st-derivative using a 3rd-order polynomial with search window of 9 (SGF-3-9)]

Funded by
NRCS-CESU

Vasques G.M., S. Grunwald, and J.O. Sickman. 2008. Comparison of multivariate methods for inferential modeling of soil carbon using visible/near-infrared spectra. Geoderma (in press).

CT

(Method: Committee Trees)



[pre-processing: Norris gap derivative with a search window of 7 (NGD-7)]

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	Model	Calibration		Validation	
		R_c^2	RMSE _C	R_v^2	RMSE _V
	SMLR	0.91	0.149	0.85	0.176
	PCR	0.83	0.212	0.83	0.189
	PLSR	0.86	0.190	0.86	0.176
	RT	0.98	0.149	0.76	0.226
	CT	0.97	0.087	0.86	0.170

VNIR – Soil Sensing

Prediction Performance – Soil 0-30 cm (n: 141) Log TC and carbon fractions [mg kg⁻¹]

SOC and fractions	Best model	Calibration		Validation	
		R _c ²	RMSE _C	R _v ²	RMSE _V
TC	LOG-PLSR	0.93	0.082	0.86	0.078
HC	SAV-PLSR	0.49	0.218	0.40	0.285
RC	SAV-PLSR	0.90	0.109	0.82	0.108
SC	SNV-SMLR	0.88	0.087	0.70	0.095
MC	SNV-PLSR	0.69	0.159	0.65	0.141

TC: Total organic carbon

HC: Hydrolysable carbon (after digestion with 6N HCl) - Thermo Electron FlashEA Elemental Analyzer

RC: Recalcitrant carbon was calculated as the difference between TOC and HC

SC: Hot water soluble organic carbon

MC: Mineralizable organic carbon

LOG: Log (1/Reflectance)

SAV: Savitzky-Golay smoothing, and averaging

SNV: Standard normal variate transformation

Florida Spectral Library (USDA-NRI)

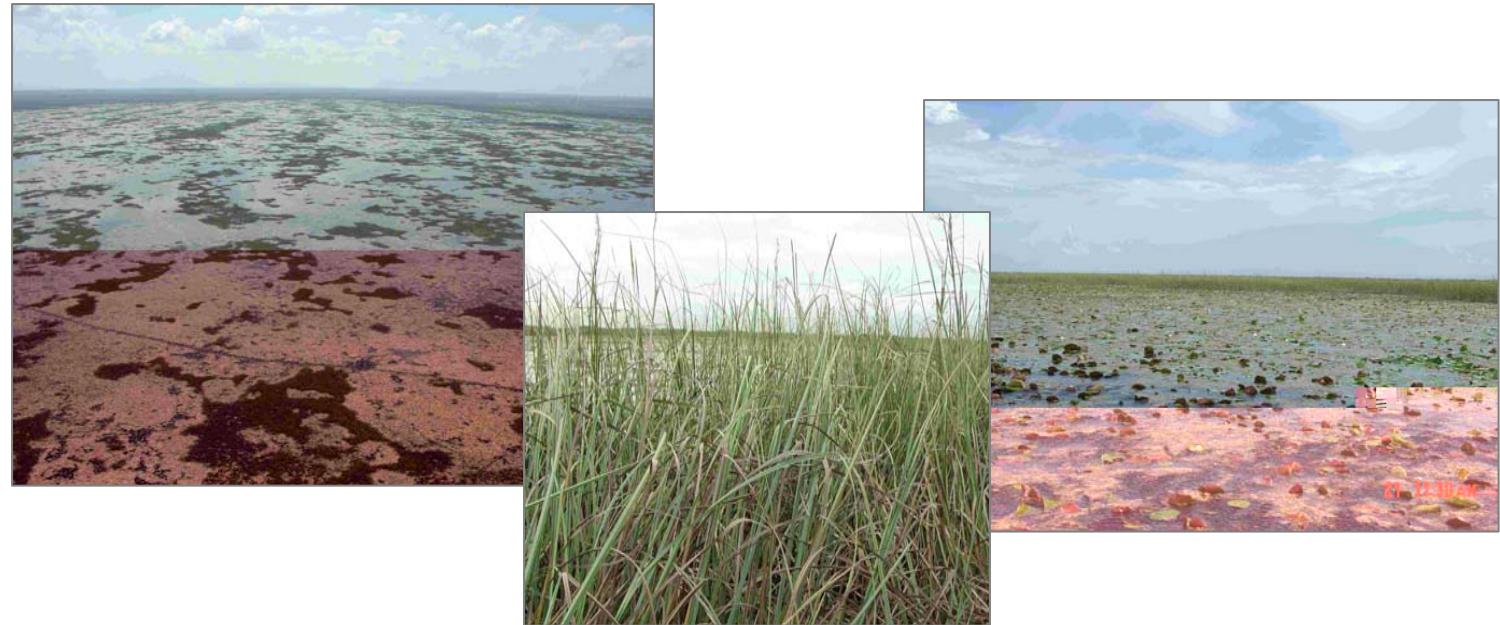


Global Spectral Library Project
Pedometrics DSM – Soil Spectroscopy Group
(Viscarra Rossel et al., 2008)
~ 27 countries are participating,
incl. UF GISSoil Group

- Accurate and rapid soil predictions of various properties (C, N, P, texture, etc.)
- Cheaper when compared to traditional analytical techniques
- On-the-go and *in-situ* VNIR
- Combinations of VNIR and other soil sensors

Objective:

Upscaling of site-specific soil data to landscape scales using statistical, geostatistical and mixed models



- Rivero R.G., S. Grunwald, and G.L. Bruland. 2007. Incorporation of spectral data into multivariate geostatistical models to map soil total phosphorus variability in a Florida wetland. *Geoderma*, 140: 428-433.
- Rivero R.G., S. Grunwald, T.Z. Osborne, K.R. Reddy and S. Newman. 2007. Characterization of the spatial distribution of soil properties in Water Conservation Area-2A, Everglades, Florida. *Soil Sci.*, 172(2): 149-166.

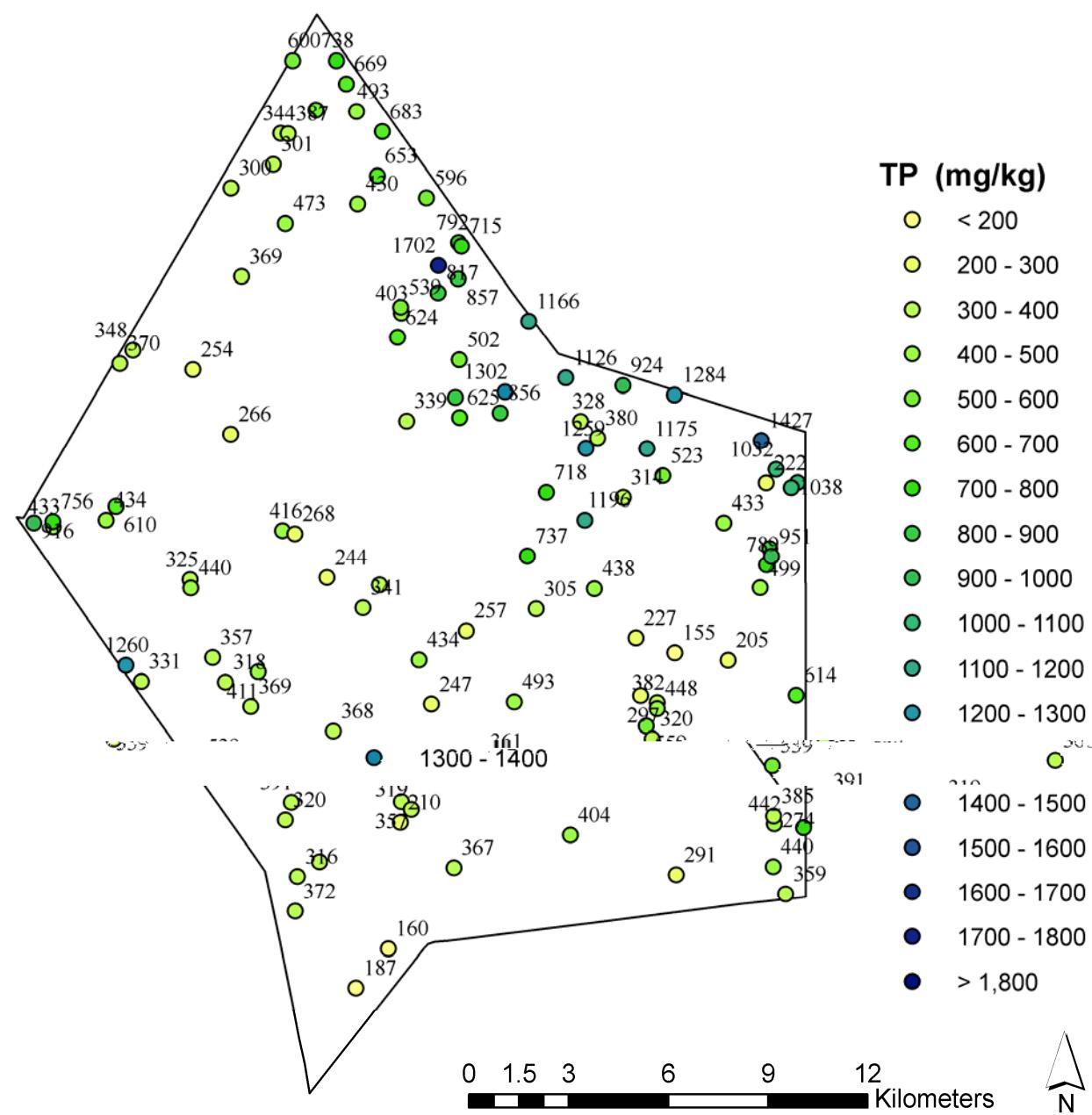
Soil Grids

Site-specific Soil Data

**Water
Conservation
Area 2A,
Everglades
(43,281 ha)**

**Soil total
phosphorus
(TP) 0-10 cm**

n: 111



DSM - Florida

Soil Grids

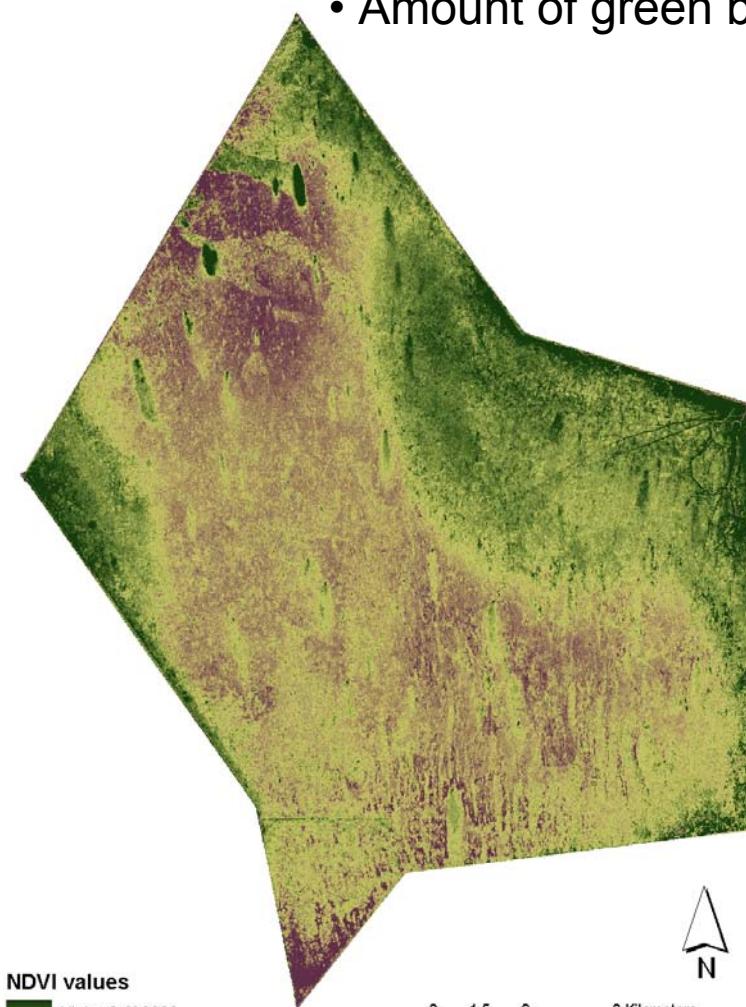
Remote Sensing Data

ASTER satellite image (15 m)
14 spectral bands from visible to
thermal infrared



Map and data processing: Rosanna Rivero
University of Florida, 2005

Normalized Difference
Vegetation Index (NDVI)
• Chlorophyll content
• Amount of green biomass



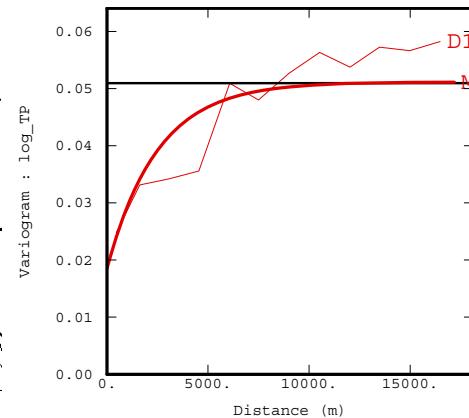
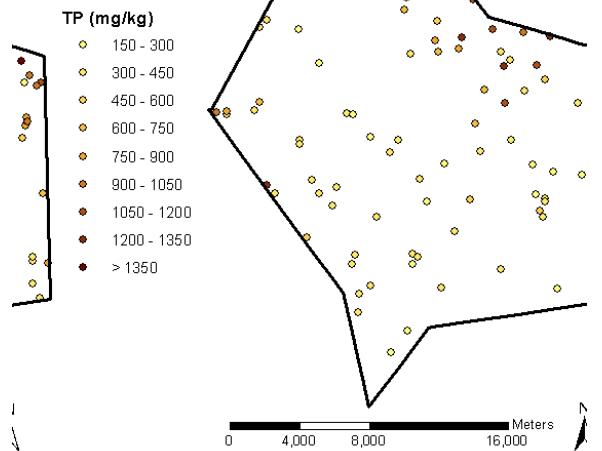
NDVI values
High : 0.632000
Low : -0.354839

Map and data processing: Rosanna Rivero
University of Florida, 2005

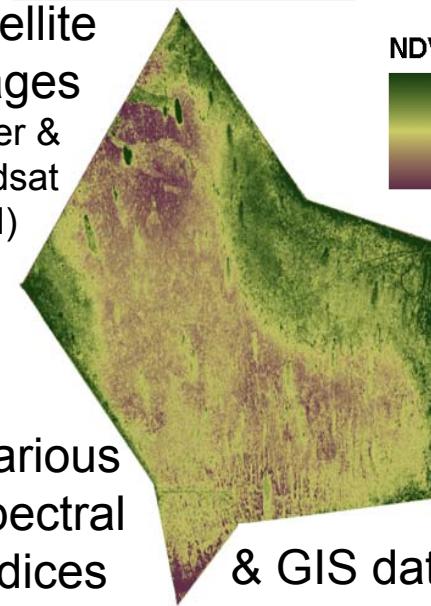
DSM - Florida

Soil Grids

TP obser-
vations



Satellite
images
(Aster &
Landsat
ETM)



Various
spectral
indices
& GIS data

Soil Grids

(1) Ordinary Kriging
using 111 TP
site observations

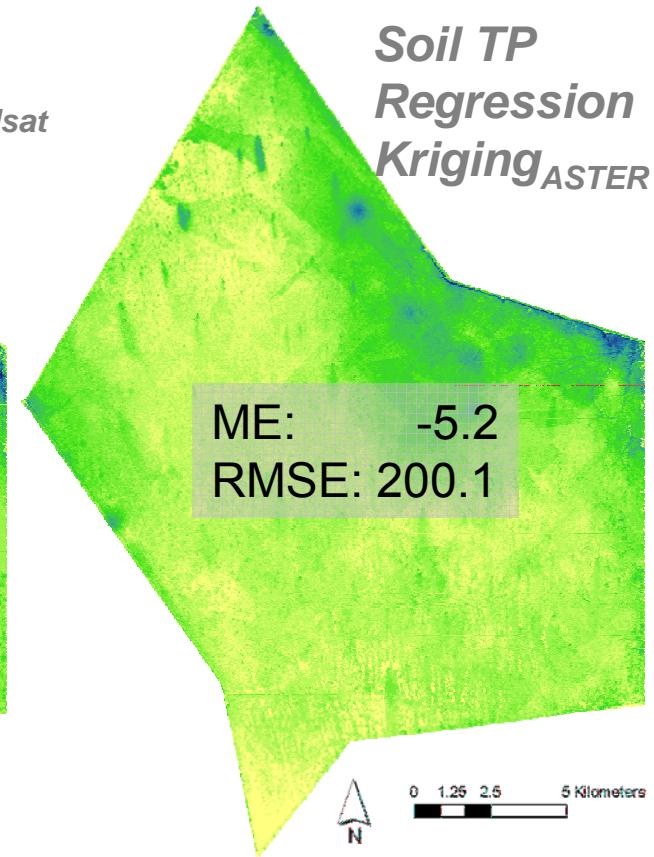
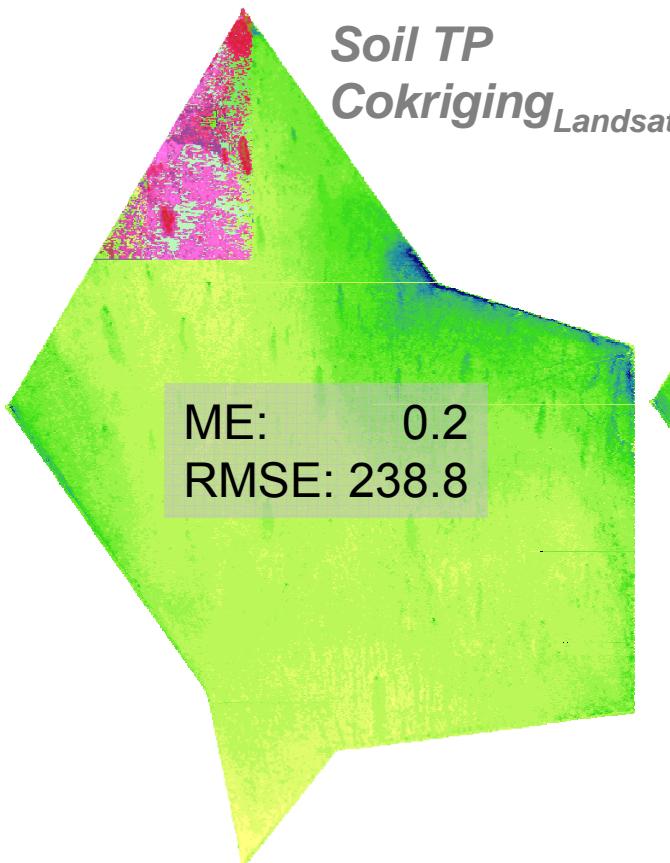
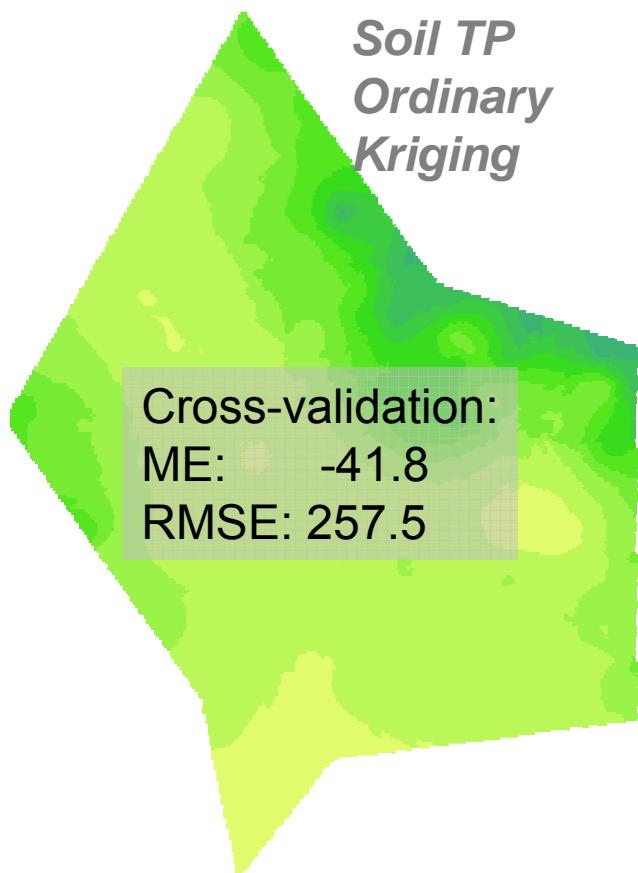
(2) Co-Kriging
using 111 TP
site observations &
satellite imagery

(3) Regression Kriging
using 111 TP
site observations &
satellite imagery &
ancillary environmental
GIS data

DSM - Florida

Soil Grids

Total Phosphorus Grids (Predictions)



Soil (0-10 cm)
TP (mg kg^{-1})

Less than 200
200 - 300
300 - 400
400 - 500
500 - 600
600 - 700

700 - 800
800 - 900
900 - 1,000
1,000 - 1,100
1,100 - 1,200
1,200 - 1,300

1,300 - 1,400
1,400 - 1,500
1,500 - 1,600
1,600 - 1,700
1,700 - 1,800
More than 1,800

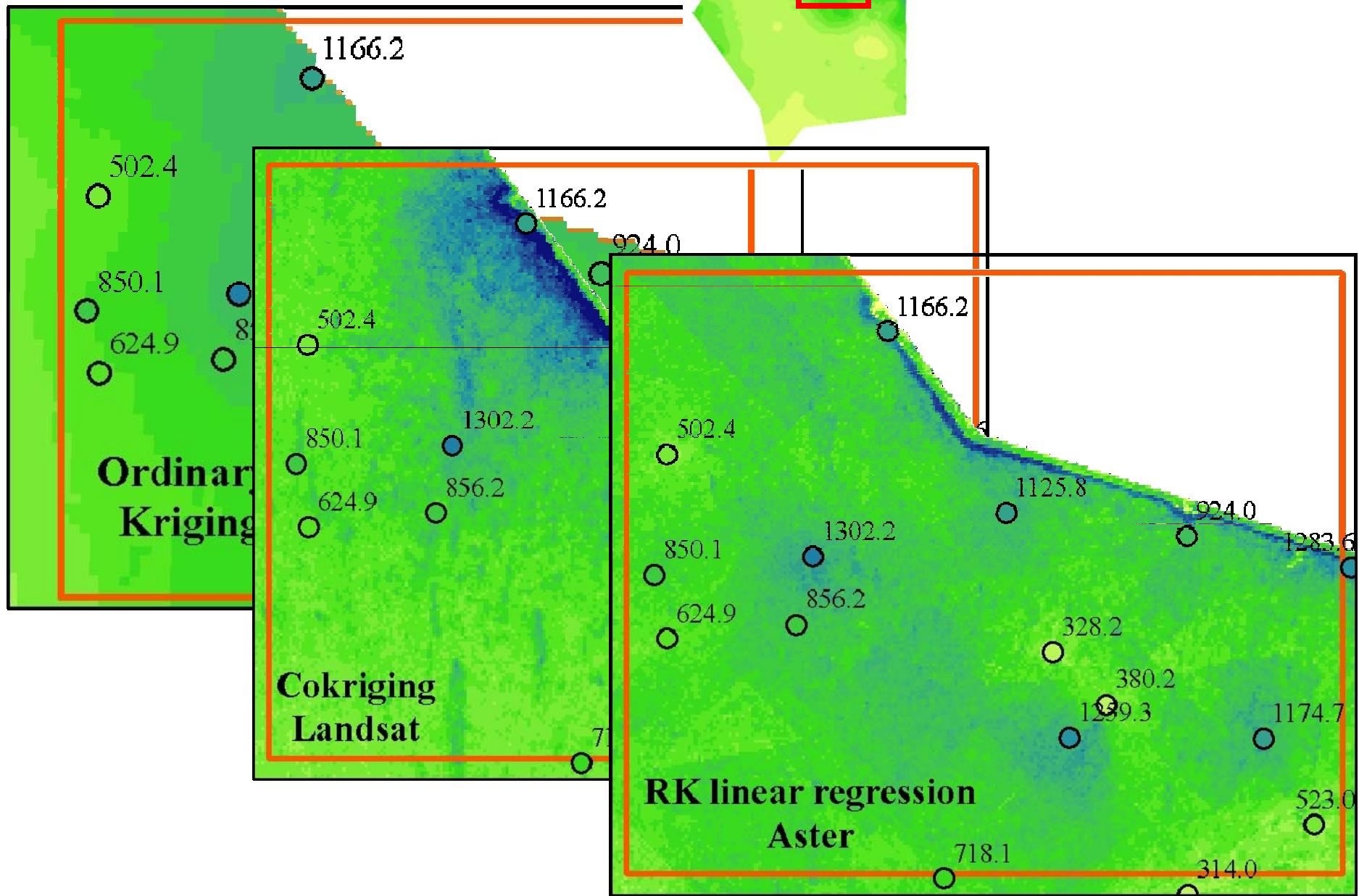
0 1.25 2.5 5 Kilometers

DSM - Florida

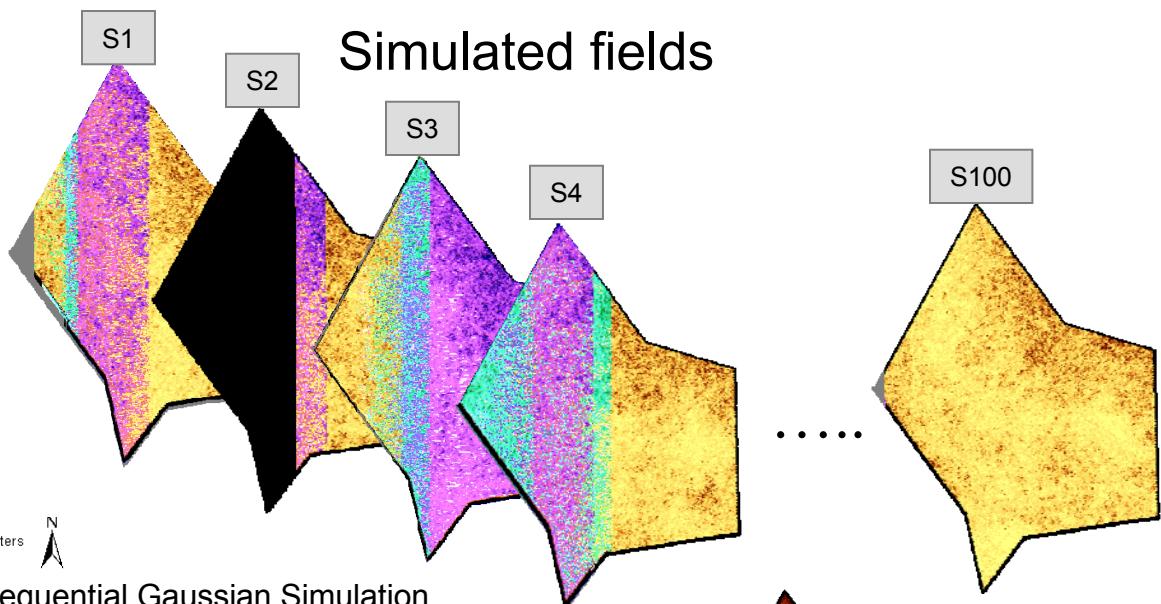
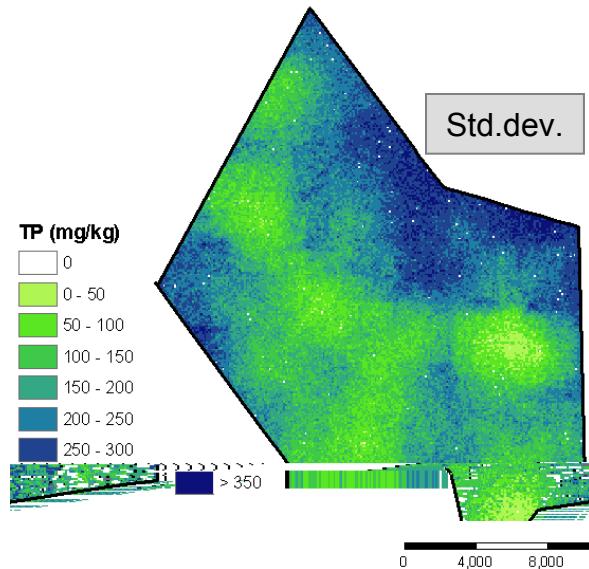
Soil Grids

Impacted

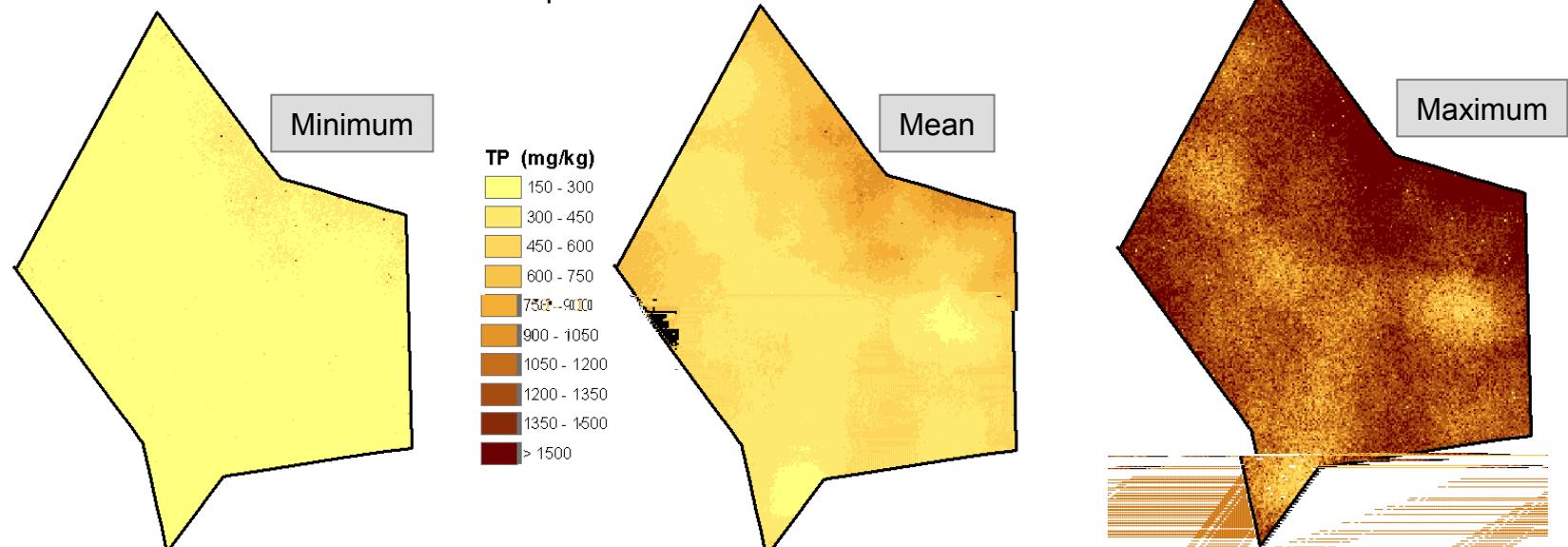
Soil TP (mg kg^{-1})



Soil Grids Uncertainty



Method: Conditional Sequential Gaussian Simulation

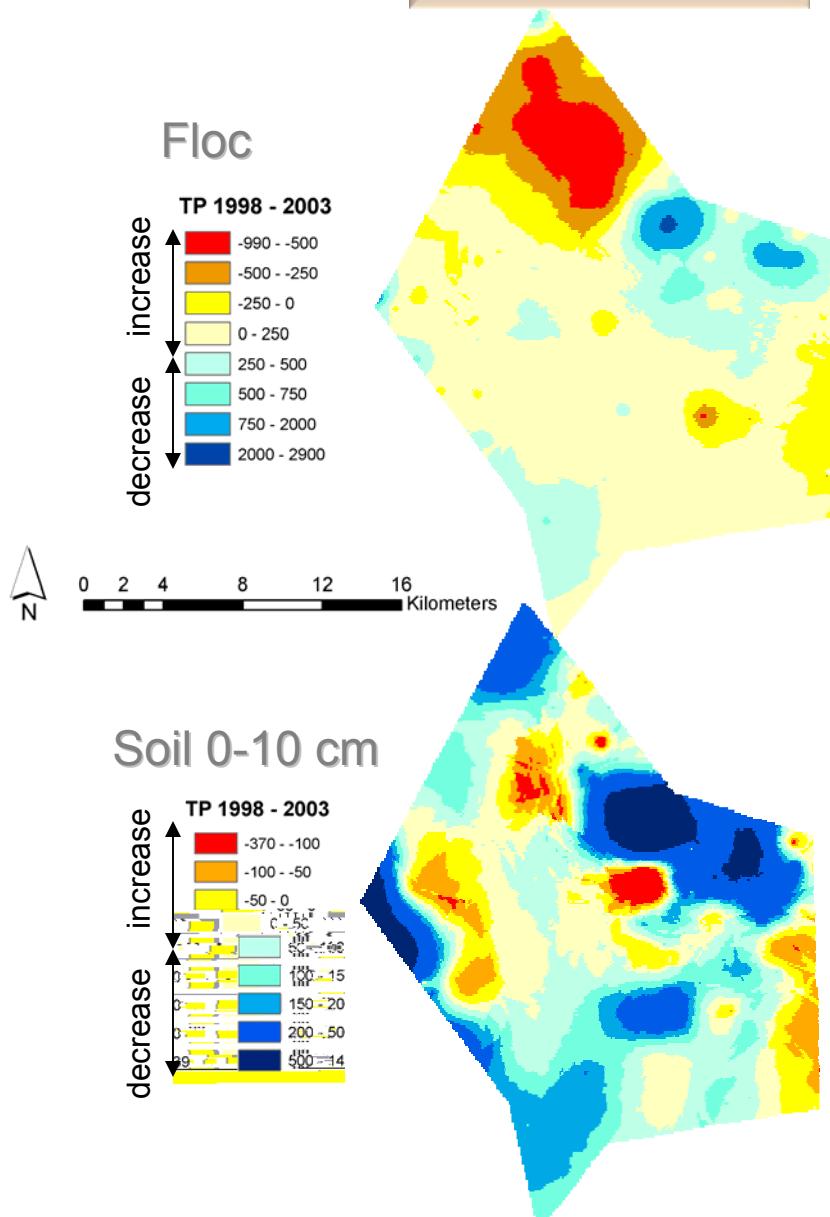


Grunwald S., R.G. Rivero and K.R. Reddy. 2007. Understanding spatial variability and its application to biogeochemistry analysis. In Sarkar D., Datta R. and R. Hannigan (eds.), Concepts and Applications in Environmental Geochemistry, Elsevier, Chapter 20, pp. 435-462.

DSM - Florida

Soil Grids

Space-Time Trajectory Analysis (1998-2003)



Error assessment
TP predictions:

Year	Layer	ME	RMSE (mg kg ⁻¹)
1998	Floc	-0.132	561.0
	Soil	-0.824	247.5
2003	Floc	0.461	206.3
	Soil	0.467	253.1

Grunwald S., T.Z. Osborne and K.R. Reddy. 200_. Temporal trajectories of phosphorus and pedo-patterns mapped in Water Conservation Area 2, Everglades, Florida, USA. Geoderma (in press).

Summary

- Soil **AND** environmental data analysis
- **Various** methods to develop soil prediction models
- Focus on **soil grids (raster)** that map the underlying soil-landscape variability
- **Error analysis** - evaluation of quality of soil predictions

Remarks

→ DSM

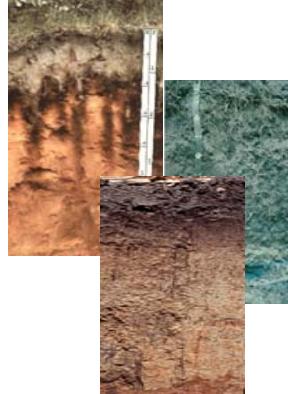
- *UF GISSoil Group* will continue to test, compare and develop DSM in terrestrial and aquatic soil-landscapes to improve their prediction qualities and accuracies ↔ Partners & Cooperators
- Use new, higher resolution remote sensors to investigate spatial scaling behavior to generate accurate and cost-effective soil prediction models

Remarks

Menace?

Myth?

Miracle?



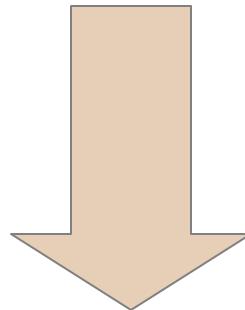
Soil

Is there a Universal Soil Equation?

Remarks

Outlook

- Transpose site-specific soil properties and processes into landscapes
- Understand soil patterns, spatial variability and covariation with environmental landscape properties



.... tremendous opportunities